The Impact of Part-Time Work on Firm Productivity: Evidence from Italy

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The Impact of Part-Time Work on Firm Productivity: Evidence from Italy

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Abstract

In this paper, we explore the impact of part-time work on firm productivity. Using a large panel data set of Italian corporations' balance sheets for the period 2000-2010, we first estimate firms' yearly productivity measures by removing the output contribution of the labor and capital inputs aggregates. We use different approaches aimed at solving input simultaneity, including a version of Ackerberg et al.'s (2006) control function approach, which accounts for firm fixed effects. We then match the productivity estimates with rich information on the firms' use of part-time work obtained from survey data for the years 2005, 2007, and 2010 and estimate the impact of part-time work on productivity. We find that a 10% increase in the share of part-timers reduces productivity by 1.45%. The results suggest that this harmful effect stems from horizontal rather than vertical part-time arrangements. We also find that firms declaring that they use part-time work to accommodate workers' requests suffer the most. Moreover, we show that the so-called 'flexible' and 'elastic' clauses are successful in cushioning the negative impact associated with part-time work.

Keywords: Part-time work, horizontal and vertical part-time work, flexible and elastic clauses, firm productivity, semiparametric estimation of production functions.

JEL: L23; L25; J23.

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1. Introduction

Since the mid-1970s, part-time work has become increasingly common, and now it represents a pervasive feature of work arrangements. According to Eurostat, about one-fifth of the total employees in Europe were working on a part-time basis in 2010 and about 67% of European firms had at least one part-time employee in 2008.

In view of the widespread diffusion of part-time work, the question of whether it is beneficial or not for firm productivity is of great relevance for both managers and policy makers. Nonetheless, only a limited number of studies have addressed this issue, while the bulk of the literature on part-time work has focused on the supply side, also in the perspective of its alleged positive role in increasing female participation in the labor market.

The theoretical literature has highlighted several channels through which part-time work may affect firm productivity. If a non-constant relationship exists between individual labor productivity and the number of hours worked, the average individual labor productivity of part-timers and full-timers will differ (Barzel, 1973). Pierce and Newstrom (1983) argue that part-timers are more productive than full-timers because part-time work relieves them from the stress associated with longer working time, while Barzel (1973) suggests that part-timers are less productive than full-timers because the working day is characterized by start-up costs. Moreover, according to the human capital theory, part-timers are less productive than full-timers due to their lower incentives to invest in human capital accumulation. The use of part-time work may also influence a firm's overall efficiency from inputs usage, or its total factor productivity (TFP). On the one hand, employing two workers on a part-time basis rather than one full-time worker leaves room for communication and coordination costs and, consequently, can reduce firm productivity (Lewis, 2003). On the other hand, organizational issues may lead part-time work to be beneficial: firms in which the activities are concentrated in only a few hours per day or firms in which the operating hours exceed the full-time working week may benefit from part-time work (Owen, 1978).

To our knowledge, only three papers have tried to assess empirically the impact of part-time work on firm productivity. Garnero et al. (2014), using a longitudinal matched employer-employee data set on Belgian private sector firms for the period 1999-2010, find that part-timers are relatively more productive than full-timers and that this effect is essentially driven by male long part-timers. On the contrary, Specchia and Vandenberghe (2013), for a similar panel of Belgian firms over the period 2002-2009, find that part-time workers are relatively less productive than their full-time counterparts. According to their estimates, a 10% increase in the share of work accomplished by part-timers lowers productivity by 1.3% for short part-timers and 0.7% for long part-timers. Künn-Nelen et al. (2013), focusing on the Dutch pharmacy sector for the year 2007, find that part-timers are relatively more productive than full-timers. A 10% increase in the share of part-timers is associated with 4.8% higher productivity. Hence, the literature on this topic is inconclusive: only 2 countries have been examined (Belgium and the Netherlands); using similar panel data for the same country, Garnero et al. (2014) and Specchia and Vandenberghe (2013) find contrasting results, while Künn-Nelen et al. (2013) focus on a very specific sector.

Our paper contributes to this limited empirical literature by considering the case of Italy and by taking on board some hitherto unexplored issues on the relationship between part-time work and firm productivity.

Our empirical analysis is based on an Italian firm-level survey - the Employer and Employee Survey (RIL) - conducted by the Institute for the Development of Workers' Vocational Training (ISFOL) in 2005, 2007, and 2010. The RIL data are uniquely rich in terms of information related to the use of part-time work in the firm, which constitutes the major reason for using this source in our analysis. The available information to estimate production functions is, instead, more limited. However, such information can be obtained from AIDA, a much larger panel data set distributed by the Bureau Van Dijk, which contains the official balance sheets of (almost) all private sector Italian corporations for the period 2000-2010. Fortunately, AIDA can be matched with RIL using the tax number of the firms (*codice fiscale*).

We conduct the empirical analysis in two steps.

In the first step, we recover estimates of firms' yearly productivity measures by removing the output contribution of the labor and capital input aggregates. For doing so, we use the AIDA data, taking advantage of its longer panel dimension (which allows us to adopt suitable methods for estimating production functions) and its large size (to increase the efficiency of our estimates). The RIL data set, instead, has only a short (three-year) panel component and about 60% of the firms are present in the data set for only one year, making it necessary to rely on the larger (both in the cross-sectional and longitudinal dimensions) AIDA data. We take care of input endogeneity issues using a modified version of the semiparametric approach developed by Ackerberg et al. (2006). This method, proposed by Vandenberghe et al. (2013), accounts for firm-specific fixed effects in the estimation of production functions. Once consistent estimates of the output contribution of capital and labor inputs aggregates are obtained, we compute for each firm and year a residual productivity measure in the spirit of TFP measures. As only the contributions of capital and *aggregate* labor (but not its constituent parts, full-time and part-time workers) are removed, our productivity measure captures the various mechanisms by which part-time work affects a firm's productivity. Then, using the tax numbers of the firms, we match the productivity estimates obtained from the AIDA data set with the RIL data set.

In the second step, we finally analyze the impact of part-time work on firm productivity for the matched RIL firms. We regress firm productivity measures obtained from the first step on indicators for the usage of part-time work by the firm, accounting for the potential endogeneity of part-time work through several empirical strategies, including OLS with rich sets of control variables, IV, and fixed effects methods.

This two-step approach differs in its implementation from the one-step methods adopted by Garnero et al. (2014), Specchia and Vandenberghe (2013), and Künn-Nelen et al. (2013), but not in the interpretation of the results. In both cases, any differential productivity impact of the two types of workers is to be interpreted as stemming from the operation of the various channels mentioned earlier, namely those related to the communication, coordination, and transaction costs that part-time work imposes on the firm (which reduce its general efficiency), as well as those more directly linked to individual productivity differences between part-timers and full-timers. In light of the data limitations that we face, our approach seems an appropriate, yet tractable, way to uncover the overall impact of part-time work on firm productivity.

Our main result is that part-time work is detrimental to firm productivity: a 10% increase in the share of part-timers is estimated to decrease productivity by 1.45%. This finding is robust across a wide set of empirical strategies that we are able to pursue with the data at hand.

Thanks to the rich information on part-time work provided by the RIL data set, we are also able to investigate some of its dimensions, which, at least to our knowledge, have not been explored previously.

In particular, we are able to distinguish between three types of part-time work: horizontal, vertical, and mixed. Horizontal part-time work, the most common kind, involves a reduction of the *daily* working time (e.g., working 5 hours per working day, instead of 8 hours per day as full-timers generally do). Vertical part-time work, on the contrary, involves a reduction of the number of working days with respect to full-timers (e.g., working 8 hours per day, but only on Monday, Tuesday, and Wednesday), while mixed part-time work combines horizontal and vertical characteristics. Our findings show that the negative effect of part-time work is exerted by the horizontal (and mixed) part-time work, whereas vertical part-time work is found to have virtually no effect on firm productivity. This result is consistent with the presence of *daily* communication and coordination costs, on the one hand, and start-up costs, on the other hand.

Moreover, we have information on whether part-time work is adopted to accommodate workers' requests for a part-time contract or, alternatively, because it satisfies firms' needs (e.g., because it is believed that part-time work better suits the production process). Our results show that part-time work has a stronger (negative) impact when the firm uses it to accommodate workers' requests.

Finally, information is available on whether the firm uses part-time work jointly with so-called 'flexible' (for horizontal part-time work) and/or 'elastic' (for vertical part-time work) clauses, instruments intended to increase the flexibility in the use of part-time work for the employer. We find evidence that such clauses make part-time work less harmful, suggesting that they may represent a good compromise between firms' and workers' needs and may eventually lead more firms to hire workers who ask for contracts on a part-time basis.

The rest of the paper is structured as follows: in Section 2, we undertake a literature review; in Section 3, we discuss the empirical model and the identification strategy; Section 4 provides a description of the Italian situation; Section 5 describes the data sets used in the analysis; Section 6 presents and discusses our results; Section 7 concludes.

2. Literature review

The academic literature on part-time work has traditionally been concerned with the supply side of the market. Using individual-level data, it has focused on investigating issues such as the determinants of part-time labor supply, its role in granting individuals (especially women) a satisfactory work-life balance, or the part-time *versus* full-time wage gap.[1]

When dealing with the demand side, both the theoretical and the empirical literature on part-time work have been more concerned with the determinants of firms' use of part-time work than with its role in affecting firm productivity (see Montgomery, 1988).

Nonetheless, the theoretical literature has proposed several theories on how the use of part-time work can affect firm productivity. In general, it is possible to distinguish among two macro categories: theories that concentrate on the impact of part-time work on the individual productivity of labor and theories that emphasize the impact of part-time work on the firm's overall efficiency from inputs usage.

The work by Barzel (1973) represents the starting point of the first set of theories. Whether part-timers are more or less productive than full-timers in the hours that they work depends on the relationship between the individual productivity of labor and the number of hours worked during the day. If the individual productivity of labor is constant across the hours of work, part-timers and full-timers are equally productive. When this constant relationship breaks down, there is room for productivity differentials between them.

[1] See, for example: Blank (1979), for an assessment of the role of part-time work in labor market transitions of women; Ermisch and Wright (1993), for a discussion on part-time *versus* full-time wage gaps of British women and on the determinants of their decision to work part-time; Gregory and Connolly (2008), for an assessment of the role of part-time work in granting work-life balance for women.

Depending on the nature of such a relationship (e.g., a positive sloped curve or an inverted U-shaped curve), part-timers may be more or less productive than full-timers. Barzel (1973), emphasizing the presence of start-up costs, according to which the individual productivity of labor is lower during the first hours of work and picks up only slowly during the day, argues that part-time workers are less productive than their full-time colleagues, essentially because part-timers stop working before full-timers. On the contrary, if one is willing to believe that the individual labor productivity increases during the working day up to a certain point, after which it starts decreasing, it turns out that part-timers may be more productive than full-timers. This is the point made by Brewster et al. (1994), who argue that long working hours, causing stress and tiredness, can make full-timers less productive than part-timers. Resorting to the human capital theory initiated by Becker (2009), another strand of the literature suggests that part-timers have fewer incentives to invest in (firm-specific) human capital. This lack of incentives, coupled with the fact that part-timers are in general less committed to career goals than their full-time colleagues (Martin and Sinclair, 2007), makes them less involved in training activities, eventually lowering their productivity levels (Nelen and De Grip, 2009).

The second set of theories emphasizes the role of part-time work in affecting a firm's overall efficiency from inputs usage, or TFP, rather than the individual productivity of labor. Several channels for this effect are proposed, which lead to contrasting results. On the one hand, Lewis (2003) argues that part-time work may give rise to coordination costs, which ultimately decrease the productivity of the firm. While the potential for these costs is lower in jobs in which workers can be easily substituted for each other (e.g., along the assembly line), it could be relevant for jobs in which task-specific skills matter (e.g., clerical work). In this case, part-time work may also create information inefficiencies and communication costs. On the other hand, papers related to the demand for part-time labor (e.g., Owen, 1978) have emphasized the allocation efficiency that part-time work may produce. In particular, firms experiencing workload peaks during certain hours or days and firms in which the operating hours exceed the full-time working hours may benefit from part-time work. Since these conditions are likely to be found in the service industry (and, especially, in the retail industry), most of the potential benefits of part-time work are to be expected for those kinds of firms. Owen (1978) also suggests that part-time work may represent a valid option when the demand facing the firm is characterized by fluctuations such that an additional full-time worker may be 'too much', while an additional part-time worker may be 'good enough'.

In conclusion, the theoretical literature has proposed various channels through which part-time work may affect a firm's productivity, with an ambiguous overall effect. At the same time, the empirical literature is scarce and has not reached yet a consensus on the sign and magnitude of the effect of part-time work. Moreover, while the theoretical literature has emphasized the distinction between the various channels at play, the empirical literature has only been able to provide estimates of the overall impact of part-time work on firm productivity, without being able to disentangle the contributions of the various theoretical channels.

A first strand of the empirical literature uses individual-level data to investigate labor productivity differentials between part-timers and full-timers by considering their differences in hourly wages.[2]. However, it is worth emphasizing that the existence of any productivity differentials predicated on the basis of these studies is only valid to the extent that labor productivity is reflected in hourly wages, an unwarranted assumption in imperfect labor markets.

A second, much smaller, strand of the literature uses firm-level data to empirically assess the impact of part-time work on firm productivity in the framework of production function estimation. To our knowledge, only three papers currently undertake such an approach. Garnero et al. (2014) use a large matched employer-employee data set for Belgium for the period 1999-2010 and a log-linearized Cobb-Douglas production function, where the share of part-time workers in the firm appears as the main regressor of interest. Their findings suggest that part-time work significantly contributes to increase firm productivity. In particular, they show that the effect is essentially driven by male long[3] part-timers, whereas the other categories, namely female long and short part-timers and male short part-timers, do not exhibit significantly different impacts compared to the reference group (i.e., full-time males). Their empirical model is based on the SYSTEM-GMM[4] estimation of the production function, following the method proposed by Hellerstein et al. (1999).

A second paper, by Specchia and Vandenberghe (2013), is again for Belgium (though for a different data set from the one used by Garnero et al., 2014) and finds, instead, that part-time work is detrimental to firm productivity. In particular, this negative effect is reported to be bigger for short part-timers than for long part-timers.[5] According to their most robust estimates, which uses the procedure proposed by Vandenberghe et al. (2013), a 10% increase in the share of part-timers causes firm productivity to decrease by 1.3% for short part-timers

[2]For example, Ermisch and Wright (1993), for British women, and Baffoe-Bonnie (2004), for the US, find a significant wage differential between part-timers and full-timers, with part-timers being paid less. Hirsch (2005) finds no significant wage gap in his US sample, after controlling for individual and job characteristics.

[3]Garnero et al. (2014) define 'long' part-timers as those working more than 25 hours per week.

[4]'SYSTEM-GMM' is the usual way in which the literature refers to the estimator proposed by Arellano and Bover (1995) and Blundell and Bond (2000).

[5]Specchia and Vandenberghe (2013) define 'short' part-timers as those whose working time is less than 55% with respect to that of full-timers and 'long' part-timers if it is between 55% and 85%.

and by 0.7% for long part-timers. They also find that the impact of short part-timers turns positive in the retail industry, suggesting that this might be a context where the beneficial effects of part-time work prevails over the detrimental effects.

Finally, Künn-Nelen et al. (2013) focus on a cross-sectional data set for the Dutch pharmacy sector, finding that part-time work significantly increases firm productivity. According to their estimates, a 10% increase in the share of part-timers is associated with 4.8% higher productivity.[6]

Since the paper by Künn-Nelen et al. (2013) concentrates on a very particular industry, our paper ends up being comparable with those of Garnero et al. (2014) and Specchia and Vandenberghe (2013), who, though analyzing the same country in (almost) the same period, obtain contrasting results.

3. Empirical model and identification

To investigate the relationship between part-time work and firm productivity, we consider the following production function:

$$Y_{it} = f(L_{it}, K_{it}; A_{it}) \tag{1}$$

where output (Y_{it}) is modeled as a function of labor (L_{it}) and capital (K_{it}) inputs aggregates and A_{it} is the residual productivity.[7]

Residual productivity should be conceived as that part of output that is not explained by the labor and capital inputs aggregates and can be thought of as a black box containing several aspects of the firm, such as its productive, organizational, and logistic efficiency. It is arguably influenced by many factors, ranging from firm strategies such as R&D investments, exports, and FDIs to the labor policies carried out by the firm, such as the use of part-time work, PT_{it}:

$$A_{it} = h(PT_{it}, ...) \tag{2}$$

There are two issues that need be clarified when using such a framework for analyzing the productivity effect of part-time work.

First, although it would be possible to examine such an effect by directly estimating (1),

[6]Using firm-level data from Switzerland and a reduced-form equation, Arvanitis (2005) assesses the relationship between sales per employee and a dummy variable indicating whether the firm employs any part-time worker, rather than the share of part-timers. He finds that the use of part-time labor in the firm is negatively related to labor productivity.

[7]Residual productivity is our measure of firm productivity. For simplicity, in the rest of the discussion we will use 'productivity', 'firm productivity', and 'residual productivity' as synonyms.

due to data limitations, we proceed in two steps, as follows. In the first step, we retrieve estimates of the residual productivity according to:

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}) \tag{3}$$

In the second step, we analyze the productivity impact of part-time work by estimating (2).

In the first step, we assume that the production function in (1) is a log-transformed Cobb-Douglas function. A relevant issue in the estimation of production functions is the potential correlation between the aggregate inputs, i.e., L_{it} and K_{it}, and the unobserved productivity level, i.e., A_{it}. For instance, a firm hit by a positive productivity shock is likely to increase its use of inputs. This issue, commonly known as the 'simultaneity problem', makes OLS estimates inconsistent. To solve this problem, several solutions have been proposed. If one is willing to assume that productivity is constant over time (i.e., $A_{it} = A_i$), fixed-effects (FE) estimation solves it. However, this assumption is controversial. Therefore, several control function methods have been developed that allow productivity to follow a more flexible (i.e., time-varying) process. Olley and Pakes (1996) (OP) are the first to propose proxying productivity through the firm's investment demand. Levinsohn and Petrin (2003) (LP) instead suggest using the firm's demand for intermediate goods as a proxy. They argue that it is more suitable than the demand for investments, essentially because it is more reactive to productivity shocks and hence more able to capture them. To solve a major drawback of the LP method, related to collinearity issues, Ackerberg et al. (2006) (ACF) propose a modified version of it, in which all the estimates of the production function parameters are obtained in the second step of the estimation procedure. Following Vandenberghe et al. (2013), we adopt a version of the ACF method that explicitly accounts for firm-specific fixed effects (ACF-FE). We argue that this procedure is more effective than ACF in delivering consistent estimates because, by removing the time-invariant unobserved heterogeneity (i.e., the time-invariant part of A_{it}), it increases the ability of the proxy to capture the unobserved firm-specific productivity level. Appendix A provides a detailed discussion on the simultaneity problem and the methods developed to solve it.

In the empirical analysis, we estimate a separate production function for each industry (as defined by the 2-digit Ateco 2002 classification) to account for the structural differences (e.g., in the production process or in industrial relation practices) among different sectors. In total, we estimate 40 different production functions. We perform OLS, FE, LP, ACF, and ACF-FE estimation.[8] All the estimations include year, region, and industry (defined

[8] OP is unfeasible for us, since we do not have (reliable) data on investments.

according to the 3-digit Ateco 2002 classification) dummies. Output (Y_{it}) is measured by the value added. Aggregate labor (L_{it}) is measured by the amount of personnel costs, including the wage bill and some fringe benefits. This is done for two main reasons. Firstly, the AIDA data are less accurate on the firm's number of employees, which is missing (or imputed) in a significant number of cases. 'Personnel costs' is, instead, an item of the the Profit and Loss Accounts that is consistently, and reliably, reported in the data. Secondly, the use the 'personnel costs' item allows us to measure the aggregate labor input more accurately, since it takes into account, at least to a certain extent, the difference in working hours between full-timers and part-timers (which we do not observe) and overcomes the problems stemming from the differences in the quality of the workforce. Moreover, the differences in the *average* hours worked by part-time and full-time workers are accounted for by our estimation of separate production functions by industry. Aggregate capital (K_{it}) is measured by the amount of tangible fixed assets.[9] Finally, the intermediate input demand (to be used in the ACF and ACF-FE procedures) is measured by the 'raw materials' item on the balance sheet.

After estimating the production functions, we compute the corresponding residual productivity estimates according to (3). In view of the considerations made previously, the productivity estimates obtained from the ACF-FE estimation are elected as our reference measure of firm productivity.[10]

In the second step, we explore the impact of part-time work on productivity. Specifically, we consider alternative specifications of the following regression model:

$$\widehat{A_{it}} = a + \theta PT_{it} + \gamma V_{it} + \delta D_{it} + u_{it} \tag{4}$$

where: PT_{it} is the number of part-timers over the firm's total number of employees and is our regressor of interest; V_{it} is a vector collecting some variables included as controls (e.g., female, non-EU, and temporary workers' shares); D_{it} is a set of dummy variables aimed at controlling for productivity differentials over time, industry (at the 3-digit level), time *and* industry (i.e., interaction dummies), region, and firm size; while u_{it} is simply the error term of the regression, possibly correlated with part-time work. In fact, one may argue that some unobservable time-invariant and firm-specific characteristics, such as managerial ability, besides contributing to determining firm productivity, also influence the amount of

[9]In particular, it is computed through a version of the permanent inventory method that applies a constant depreciation rate (0.065) to tangible fixed assets.

[10]A robustness analysis using alternative productivity estimates (i.e., those deriving from OLS, FE, LP, and ACF estimations of the production functions) is conducted in Appendix D.

part-time work actually used. One may think that more skilled managers, while allowing firms to reach a higher level of productivity, are also more prone to accommodate workers' requests for shorter working time. Similarly, one may argue that the use of part-time work is influenced by productivity shocks. It may be the case, for instance, that in bad times firms 'convert' some of their full-time employees into part-timers to avoid firing them. The practical relevance of such concerns will be assessed by comparing the OLS estimates with those obtained with fixed-effects (FE) and instrumental variable (IV) regressions.[11]

The second issue that we need to clarify relates to the nature of the estimated effect of part-time work. As mentioned earlier, many theoretical channels operate behind the overall estimated impact, and the current empirical literature - including our paper - does not disentangle the various channels at play. For instance, it is difficult to empirically assess whether any differential productivity effect of part-time versus full-time workers derives from firm-wide coordination or organizational inefficiencies related to the use of part-time work, or derives, instead, from individual-level productivity differences related to a non-linear relationship between stress, fatigue, or start-up costs and the number of hours worked by the individual. Our first-step productivity measure is obtained by removing the output contribution of the composite labor index (and of the capital input aggregate), which is the only one available in AIDA (i.e., no information on the share of part-time employees is available in this data source). Hence, such a residual productivity measure reflects the operation of the various channels mentioned earlier.[12] While a channel disentangling them remains an important task for future research, the current paper sets itself a more limited task, namely, to contribute to the inconclusive empirical literature on the *overall* impact of

[11]The ACF-FE estimation carried out in the first step of our procedure does not solve any endogeneity problem related to part-time work in the second step. It (only) helps to get consistent estimates of β_l and β_k, and, consequently, of the residual productivity. Indeed, productivity estimates used as dependent variable in the second step embed both the unobserved heterogeneity and the productivity shock, which, in the second step, flow into u_{it}. This is the very reason for which we perform FE and IV estimations in the second step, over and above simple OLS.

[12]Instead of entering the share of part-time work in A_{it}, an alternative is to assume that part-time and full-time workers enters additively (i.e., as perfect substitutes) in a labor aggregate, but with a potentially different labor productivity (i.e., $L_{it} = FT_{it} + \gamma PT_{it}$, where FT_{it} and PT_{it} represent respectively the number of full-time and part-time workers and γ expresses the relative productivity of the two types of workers), as proposed by Hellerstein et al. (1999). In this case, too, γ clearly captures the operation of both firm-wide coordination costs, as well as intrinsic differences in individual productivity of part-time versus full-time workers. Notice also that, were one to additionally assume that A_{it} is a linear function of the share of part-timers, i.e.,$A_{it} = \beta_0 + \beta_1 PT_{it}$, the separate effects of β_1 and γ would not be identified in the context of the log-linearized Cobb-Douglas production function of Garnero et al. (2014), Specchia and Vandenberghe (2013), and Künn-Nelen et al. (2013). More general production functions might in principle allow for the identification of the two separate effects. However, in the absence of hard data on individual productivity of labor, as opposed to firm-level productivity, this task is rather demanding and is not currently pursued in the literature.

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4. The Italian case

In all industrialized countries, including Italy, part-time work started to be used increasingly in the middle of the 1970s. As Kalleberg (2000) points out, the main determinants of its constant growth can be found in the increased uncertainty of the general economic conditions and in the (consequent) sharpened competition among firms, which eventually led them to prefer flexible working arrangements, such as part-time and temporary work. At the same time, national labor laws, often designed to protect standard workers (i.e., full-time and permanent), contributed to the growth of part-time work, intended as a way for firms to escape the costs and legal duties associated with these laws. Demographic changes in the composition of the labor force have played a fundamental role, too: the rises in married female workers and older workers, attracted by the flexibility characterizing part-time work, are the two most straightforward examples.

According to Eurostat, about 19% of European employees worked part-time in 2010. In Italy, the share of part-time workers was around 15%, a percentage similar to that of Spain and France.

Many studies stress that part-time work acts as an instrument of work-life balance, allowing people to conciliate work better with their private life needs. Since women are usually the ones involved in family care and household activities, it is not surprising that the great majority of part-time jobs are accounted for by women. Similarly to the rest of Europe, in Italy, the incidence of part-time work among employed women was around 29% in 2010, while about 6% for men.

Data provided by the ISFOL[13] show that part-timers are over-represented in young age groups and that female part-timers are over-represented in the central age category, presumably because this is the age at which women have children. Although the incidence of part-time work is largest among the low-educated category for women, the contrary applies to males. While part-timers are generally segregated into low-skilled jobs, in the trade and services sectors they are over-represented in high-skilled occupations. Finally, part-timers are segregated into temporary contracts and into the trade and household services sectors.

According to the OECD, in 2010, about 40% of Italian part-timers declared themselves to be employed on a part-time basis against their will. Together with this involuntary part-time employment, a phenomenon exists that can also be referred to as 'involuntary

[13] In particular, we are referring to the ISFOL PLUS 2008, a large survey conducted on about 40,000 Italian women and men.

part-time' employment to all intents and purposes. Many firms[14] use part-time work to accommodate workers' requests for shorter working hours and would prefer to employ their part-time workers on a full-time basis. The fact that many part-timers would prefer to work full-time, while, at the same time, many firms employing part-timers would prefer to employ them on a full-time basis, highlights a substantial misalignment between the demand and the supply of part-time labor, which eventually leads to dissatisfaction among many workers and firms.

In Italy, part-time work received its first, bare regulation only in 1984. Subsequently, thanks to the implementation of the European Directives concerning part-time work, it has been regulated more systematically on several occasions: in 2000, in 2003 (with the so-called 'Biagi's law'), and in 2007.

The regulation of part-time work is based on the principle of equal treatment between part-time and full-time workers, both in relation to the hourly pay and annual leave and in relation to other kinds of non-monetary benefits. According to the Italian legislation, the reduction of working hours can occur in three ways: the horizontal model, in which the employee works all the working days with a reduction in the daily working time; the vertical model, in which the employee works full-time, but only on some days of the week, month, or year; and the mixed model, which is a combination of the horizontal and the vertical part-time model. Part-time work contracts must contain a clear and precise determination of the working time with respect to the day, week, month, and year. Working time can be made flexible through the use of so-called 'flexible' and 'elastic clauses'. Flexible clauses give the possibility to modify the *collocation* of the daily working hours in the case of horizontal part-time contracts, whereas elastic clauses can be used for extending (and not curtailing) the number of working hours in vertical part-time contracts. The procedures for the use of such clauses are provided by the law and by the sectoral labor collective agreements applied to the specific productive unit.

The general trend in the regulation of part-time work has been, on the one hand, in the direction of a systematic and structured discipline and, on the other hand, toward the attainment of greater flexibility and discretion in the signing of part-time work contracts. Compared with the early regulations, the 2003 Biagi's Law and, less extensively, the 2007 legislative decree have granted greater flexibility in the working time arrangements and have reduced the restrictions on carrying out additional/overtime work and on stipulating flexible or elastic clauses. Moreover, they have left an active role to collective bargaining in integrating the legal regulation and concretely ruling part-time work. However, as we shall

[14] According to the 2010 RIL survey, they are about 60% of those using part-time arrangements.

see later in the discussion, the legislative decree in 2007, though generally oriented toward increasing part-time work flexibility, significantly reduced firms' prerogative in relation to the signing of the elastic and flexible clauses introduced by Biagi's Law.

5. Data

To assess the impact of part-time work on firm productivity, we use the three available waves of the RIL survey, for years 2005, 2007, and 2010. Each wave of the survey interviews over 23,000 private sector Italian firms, including both partnerships and corporations. The data are uniquely rich concerning the composition of the workforce, including the fraction of part-timers and, among them, of horizontal, vertical, and mixed part-timers. Moreover, they provide information on the reasons for which the firm uses part-time work and on the use of flexible and elastic clauses. Finally, the data provide an extensive set of firm-level controls, including management characteristics and the gender, age, and education distribution of the workforce.

Note that, in the empirical analysis, we restrict our attention to firms with at least 10 employees, so as to consider firms with a minimal organizational structure and meaningfully compute the shares of employees in different work arrangements.

While the RIL data set provides accurate information on employees, the data on revenues, physical capital, and intermediate inputs are incomplete or completely absent. Hence, to perform our production function estimation, we have to resort to another data set. For this purpose, we use the AIDA data provided by the Bureau Van Dijk for the period 2000-2010. The data provide comprehensive information on the official balance sheets of (almost) all the Italian corporations operating in the private sector, except for the agricultural and financial industries. The data contain yearly values of variables such as revenues, value added, net profit, book value of physical capital, total wage bill, and raw-materials expenditure, as well as information on the location of the firm and its industry affiliation (defined according to the Ateco 2002 classification).

Fortunately, the RIL firms can be matched with the balance sheet information from AIDA through the firm tax number (*codice fiscale*), which uniquely identifies each firm in both data sets.

Since only a small sub-sample of the RIL firms is followed over time, making the (complete) RIL data set only partially panel, we prefer to estimate the impact of part-time work on firm productivity through the two-step procedure described before.[15]

[15] If we would have adopted the one-step procedure in Vandenberghe et al. (2013), we would have been forced to restrict our analysis to only about 25% of the RIL observations, since only firms with at least two

Using the AIDA data set to obtain the productivity estimates offers a number of advantages. Thanks to its width (about 2.5 million observations), it is still possible to gain precise estimates while estimating 40 different production functions. Moreover, the relatively long panel improves the performance of the methods that exploit the within-firm variation (e.g., ACF-FE). To minimize attenuation biases related to measurement error, we carry out an essential cleaning procedure, as is typically performed in the literature on the estimation of production functions from balance sheet data. Appendix B provides a detailed description of this procedure and reports some summary statistics of the AIDA data set.

We finally match the residual productivity estimates recovered from AIDA with the RIL's firms. We will refer to the resulting data set as the 'RIL-AIDA' data set. Out of 22,696 firm-year potential matches, 14,889 are actually matched with the productivity estimate from the AIDA data set, resulting in a merge rate of about 66%. This result should be considered in view of the following facts. On the one hand, AIDA does not contain data for agricultural and financial firms, while RIL does. On the other hand, besides the basic cleaning procedure described in Appendix B, we are forced to remove from AIDA any observation with missing, negative, or zero values of the variables used in the production function. Moreover, to perform the semiparametric methods described before, we need to restrict the attention to the AIDA firms with at least two *consecutive* years of observations.[16] Finally, we cannot exclude coding errors in the reported tax number from either data sets, errors that we expect to be random.

The final version of the RIL-AIDA data set used in the second step is made up of 13,860 firm-year observations for 9,405 firms.

The top panel of Table 1 shows that the manufacturing sector is by far the largest, accounting for almost 50% of the observations. The services and trade sectors represent, respectively, 17.2% and 10.6% of the observations, while the rest of the sample is split between the construction sector (14.4%) and the transportation and telecommunication industry (8%). The lowest panel of Table 1 shows that for about 63% of the firms we have only 1 observation: this is due to the partially-panel nature of the RIL data set. About 26% of the firms are observed over 2 periods, while about 11% of them are observed over 3 periods.

Table 2 presents some summary statistics of the RIL-AIDA data set. On average, firms' revenues are around 33 million euros per year. The average number of employees in the

consecutive observations could have been kept.

[16] Indeed, when considering the merge between the corporations with at least 10 employees in the RIL panel with the original version of the AIDA data set, i.e., without any variable cleanings, the merge rate increases to about 93%. Still, the match is not full because we are not able to remove agricultural and financial firms from the RIL panel (in the RIL data set we observe industry classification with many missing values).

firms is about 104, but for half of them (75%) this figure is less than 29 (69), consistently with the Italian industrial structure in which small- and medium-sized firms represent the great majority of firms. On average, about 31% of employees are female and about 6% originate from non-EU countries, while 10.5% are employed on a temporary basis. About 59% of employees are blue-collar workers, 36.1% are white-collar workers, and about 5% fill a managerial position. The great majority of workers in the average firm have a low or medium level of education, while only 8.8% of them have a college degree; on average, about half of the workforce is aged between 35 and 49 years.[17]

On average, firms employ 8.4% of their workforce on a part-time basis. In the average firm, 79.1% of part-timers are women, while only 20.9% are men, in line with the fact that part-time positions are mainly occupied by women. Horizontal part-time work is by far the most widespread type of part-time work used by firms: in the average firm, 86.8% of part-timers have a horizontal part-time contract, while only 7% and 6.2% are vertical and mixed part-timers, respectively. In particular, female horizontal part-time employees represent the most common type of part-timers, accounting for about 70% of the total part-timers in the average firm.

Table 3 shows that part-time work is used by the great majority of firms: about 68% of them employ at least one worker on a part-time basis. On the contrary, the use of elastic and/or flexible clauses is not so pervasive: only around 37% of firms using part-time work adopt these clauses. Excluding firms using mixed part-time work, it is possible to notice that the incidence of clauses varies according to the type of part-time work: about 34% of firms using horizontal part-time work apply flexible clauses, while about 39% of firms using vertical part-time work apply elastic clauses.[18] The bottom panel of Table 3 summarizes the answers given by firms employing some part-timers regarding the main reason for their use of part-time work. The vast majority of them (68%) declare that they use part-time work to accommodate workers' requests for shorter working time.[19] The remaining fraction is split between those that use it willingly (30%) and those that give answers that differ from the proposed alternatives (2%). Among the firms that declare that they use it willingly, the main reasons concern the suitability of part-time work for the production process (20.7%) and the impossibility of employing workers full-time because of budget constraints (4.8%). Only a few firms choose part-time work because they believe that part-timers are more productive

[17] Data on the education and age distribution of the employees in the firm are available only for 2010.

[18] Since mixed part-time work is a combination of horizontal and vertical part-time work, both flexible *and* elastic clauses can be applied in this type of contract. Whereas, flexible clauses *only* apply to horizontal part-time work, while elastic clauses *only* apply to vertical part-time work.

[19] This happens in all the macro-industries, i.e., manufacturing, construction, trade, transportation and communication, and services.

than full-timers (2.5%) and to face programmed seasonality (2%).

6. Results

6.1. Main findings

In this section, we explore the impact of part-time work on firm productivity, focusing on the second-step equation in (4). We refer the reader to Appendix C for details on the productivity estimates obtained in the first step.

Table 4 presents the results from 11 different specifications of and/or methods to estimate Equation (4). Recall that, since our preferred estimation method for the first step is ACF-FE, we use the ACF-FE productivity estimates as the dependent variable in all the following second-step estimations.

The first column shows the OLS estimates of Equation (4) which includes only a basic set of controls: dummies for firm size, year, region, industry, and year/industry interactions. According to this initial regression, part-time work has a strongly significant negative impact on firm productivity: a 10% increase in the share of part-time workers reduces firm productivity by 2.17%, i.e., $(e^{-0.219*0.10} - 1) * 100$.

However, as we pointed out in Section 4, since part-time workers tend to be segregated in relation to gender, job, and type of contract (i.e., temporary *versus* permanent), it is safe to control also for these workforce characteristics. This is carried out in Specification 2, which adds the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers to the list of controls already included in Specification 1. According to this model, part-time work still has a negative and significant impact on productivity, though it is smaller: a 10% increase in its share brings about a reduction in the firm productivity of about 1.45%. The results suggest that, besides being (in general) positively correlated with the share of part-timers[20], these workforce characteristics are negatively related to firm productivity. Thus, if we fail to control for them, we tend to overestimate the negative impact of part-time work.

Moreover, the available empirical evidence suggests that part-timers might also be segregated by age and education. Even though we are not able to account for the age and education distribution of the workforce for the whole sample period, we can do so for year 2010 (Specification 3). As discussed in Section 3, the characteristics of the management may also influence both the level of part-time work and the firm productivity. Albeit only for

[20] In the sample, the shares of females, white-collars, non-EU workers, and temporary workers are positively correlated with the share of part-timers, while its correlation with the share of blue-collars is negative although very small (-0.006).

year 2010, we are able to account for several managerial characteristics: the manager's type (i.e., whether he or she is the owner of the firm or an internal/external manager), gender, education, and age (Specification 4). Comparing Specification 5, which reproduces Specification 2 but only for year 2010, with Specifications 3 and 4, we can see that these sets of controls do not substantially change the estimate: -0.182 in both 3 and 4 *versus* -0.192 in 5.

Despite our specifications already control for a rich list of potentially confounding factors, one may still be concerned that unobservable firm heterogeneity (e.g., managerial ability) might preclude the identification of the effect of interest. One way to investigate whether this is the case is to compare our previous findings with those obtained from a FE estimation of Equation (4), thereby removing the omitted variable bias arising from time-invariant unobserved heterogeneity. According to the FE Specification 6, which only includes year and year/industry interaction terms, the effect of part-time work on firm productivity is still negative and significant at the 10% level. The FE Specification 7 adds the usual workforce controls, specifically, the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers. The estimated coefficient is very similar to the first FE specification (-0.115 *versus* -0.117) and still significant at the 10% level. For comparative purposes, Specification 8 performs an OLS regression as in 2 but on the sample used in the FE estimation. The estimated impact of part-time work is still negative and significant, albeit a little higher in absolute terms than the FE one (-0.169 *versus* -0.117). When assessing these results, it should be noted that FE estimates are known for delivering coefficients biased toward 0, because of the exacerbation of the measurement error induced by the within-firm transformation. Regarding the higher p-value of the part-time work coefficient in the FE estimates compared to OLS ones, it should be noted that the FE method can only be performed on a much smaller sample and with limited within-firm variation due to the short longitudinal dimension of the RIL data.

As discussed in Section 3, an additional concern is that part-time work might be correlated with idiosyncratic productivity shocks to the firm, causing part-time work to be endogenous and hindering the identification of the impact. To explore this possibility, we perform a simple IV estimation of Equation (4), in which we instrument part-time work with its 2- or 3-year lag. In practice, in the equation for the year 2010, we instrument the share of part-timers with its level in 2007, and in the equation for the year 2007, with its level in 2005. Notice that to perform this kind of IV estimation, we lose one year of observations, that is, 2005, and we are forced to consider firms with at least 2 years of consecutive observations. This sharply reduces our sample to only 3,536 observations. The results of this IV estimation are presented in column 9 of Table 4. The estimated impact of part-time work is still negative, significant at the 1% level, and equal to -0.273.[21]

Since this model is exactly identified, we cannot assess the validity (i.e., the exogeneity) of the instrument used. To gain insights into this issue, we perform another IV estimation that, besides instrumenting part-time work with its own lag, adds other instruments constructed on the basis of the method proposed by Lewbel (2012). This approach serves to identify parameters in models with endogenous regressors, when external or internal instruments are lacking, or, alternatively, to gain overidentification for testing the validity of the orthogonality conditions. Identification is achieved by having instruments that are uncorrelated with the product of heteroskedastic errors. In practice, the first step is to run an OLS regression on the endogenous regressor (share of part-time workers, in our case) against all the exogenous regressors in the model. Then, the residuals obtained from this regression are used to construct the instruments from:

$$Z_j = (X_j - \bar{X}) \cdot \epsilon \tag{5}$$

where ϵ is the vector of the first-stage residuals, X_j is the vector of observations for the exogenous regressor j, $\bar{X}$ is its mean, and Z_j is the instrument generated from regressor X_j. Besides the lag of the part-time workers' share, we use 5 additional instruments constructed on the basis of Equation (5) from the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers. With these 6 instruments for the share of part-timers, we can then perform the standard IV estimation (Specification 10). The estimated coefficient is again negative, significant at the 1% level and equal to -0.252. The Hansen-J test for the validity of the overidentifying restrictions indicates that they are valid overall (p-value 0.692).

As before, for comparative purposes, we run an OLS regression on the sample used in the IV estimation (Specification 11), finding similar estimates (-0.195) for the coefficient of part-time work. Comparing the IV and OLS estimates, we conclude that the potential correlation of part-time work with time-varying productivity shocks is unlikely to represent a major issue for our results in practice.

Before considering a number of robustness checks and extensions, we briefly discuss the association between firm productivity and the other regressors included in the analysis. Increases in the shares of females[22], non-EU workers, and blue- and white-collar workers (with

[21] Lagged share of part-timers is a strong predictor of current share of part-timers (the associated coefficient is 0.709 with a standard error equal to 0.021), with a first-stage F statistic well above conventional threshold levels (1,106.712).

[22] We have also performed estimations for the separate impact of female and male part-timers. According to the usual OLS estimates (Specification 2 of Table 4) both female and male part-timers have a significant and negative impact, with similar magnitudes. According to the FE estimates (Specification 7 of Table 4), only female part-timers significantly decrease firm productivity, while the impact of male part-timers is

respect to managers) are generally associated with a decrease in productivity. On the contrary, the share of temporary, young (under 35), and highly educated workers is positively correlated with productivity. Our results also suggest that having an internal/external manager is more beneficial to a firm's productivity than when the owner of the firm also manages it. A negative association is also detected between productivity and female managers, as is the case of young managers (under 40). The results also suggest that productivity increases with the firm size.

Appendix D provides some robustness checks. First, we compare the estimated impact of part-time work on productivity when different productivity estimates are used. Second, we consider the impact of interest only for the period before the crisis (i.e., the years 2005 and 2007). Our main results remain broadly unchanged.

To summarize, we find that part-time work is detrimental to firm productivity. Our estimates are in line with those reported by Specchia and Vandenberghe (2013) for Belgium. In particular, while they find that a 10% increase in the share part-timers causes firm productivity to decrease by 1.3% (0.7%) for long (short) part-timers, we find the same figure to be slightly higher: 1.45%.[23]

We also find that not accounting for the age and education distribution of the workforce and management characteristics, on the one hand, as well as unobserved firm-specific fixed effects and the correlation of part-time work with productivity shocks, on the other hand, is unlikely to represent a real threat to the identification of the effect of interest. In view of this consideration and given that OLS estimation allows us to exploit the full sample, we take Specification 2 as our reference, both for assessing the effect of part-time work on firm productivity, as just discussed, and for our extensions, which are discussed below.

negative but non significant. A possible explanation for this lack of precision may reside in the fact that relatively few firms employ male part-timers (about 29%). This set of results is available upon request.

[23]While we are not able to directly distinguish between long and short part-timers in the RIL data set, we have tried to account for differences in the working time of part-timers indirectly. We have resorted to the ISFOL PLUS, an individual-level data set for the years 2005, 2006, 2008, and 2010 that is provided by the ISFOL. The ISFOL PLUS data set contains extensive information on a representative sample of Italian individuals aged between 15 and 64. In particular, it provides information on whether the individual works on a full-time or part-time basis and on the number of hours worked during the week. Therefore, it has been possible to generate an indicator of the working time of part-timers relative to full-timers by gender, sector of economic activity, and year (years 2006 and 2008 of ISFOL PLUS have been put together to generate values referred to year 2007 in RIL). Finally, we have applied such indicators to get a full-time equivalent share of part-timers and conducted the usual set of estimates. Results confirm that part-time work is detrimental to firm productivity, along the full set of specifications of Table 4 (i.e., OLS, FE, and IV). Results are available upon request.

6.2. Extensions

Until now, we have found that part-time work generally dampens firm productivity. This finding is coherent with the idea that part-time work causes communication, organizational, and start-up costs, which eventually translate into productivity losses.

We now concentrate on some extensions, which, at least to our knowledge, have never previously been explored.

Table 5 shows the OLS estimates of the separate impacts of horizontal, vertical, and mixed part-time work. Not surprisingly, since it represents most of the part-time work, horizontal part-time work is estimated to have virtually the same impact as already shown for the general case (-0.148 *versus* -0.146). This result is strongly significant (at the 1% level). Vertical part-time work is also estimated to have a negative impact, though very small in magnitude (-0.013) and not significantly different from zero at any conventional level. This result suggests that what really dampens firm productivity is working shorter hours each day, while working full-time on only some days of the week (or month) does not seem to do so. The presence of start-up costs and communication costs on a *daily* basis might be the explanation for this finding. Mixed part-time work is predicted to have a negative and significant impact on firm productivity (-0.197): being a mixture of the horizontal and vertical model, it is presumable that its effect stems from the horizontal component.

In Table 6, we analyze whether the productivity impact of part-time work is different if the firm passively accepts it as a consequence of workers' requests for shorter hours compared to the case in which the firm actively chooses to use it. To answer this question, we divide the sample of firm-year observations using part-time work into two sub-samples: those using part-time work as the result of workers' requests and those that choose to adopt it.[24] The results are consistent with our conjecture: the firms that are 'forced' to use part-time work are the ones that suffer the most from it. Indeed, a 10% increase in the share of part-timers is estimated to reduce productivity by about 2.51% in this case. On the other hand, the reduction in productivity is only 1.35% for the case in which firms willingly choose to use part-time work. What is surprising is that part-time work is also harmful to those firms that willingly choose to adopt it.[25] One possible explanation for this might be that managers fail to fully anticipate the detrimental impact of part-time work. However, it may also be the result of a consciously weighed trade-off between productivity losses and costs savings if

[24]Notice that we have to remove observations that use part-time work but choose the 'other reason' item, since we do not know whether they belong to the first or to the second group.

[25]Even removing from the sample firms declaring to use part-time work because they cannot afford to keep the workers on a full-time basis, which, in a sense, makes them forced to use it, does not change the result.

part-timers are discriminated against in terms of hourly pay.

Table 7 investigates whether the impact of part-time work on firm productivity is different if the firm utilizes elastic and/or flexible clauses. As before, we split the sample of firm-year observations using part-time work into two groups: those that use part-time contracts with clauses and those that do not. We find evidence that using such clauses helps in cushioning the negative effect of part-time work. They contribute to reducing its negative impact by about 43%. In particular, a 10% increase in the share of part-timers is estimated to bring about a decrease in productivity by 1.09% in the case in which the clauses are used, whereas the same increase causes productivity to decrease by 1.89% in the case in which they are not used. These results shed light on the role of such clauses as instruments intended to increase the flexibility for the firms in the use of part-time work and, hence, to make them more willing to use it, while allowing individuals to conciliate better their work and private life.

To gain further insights into the potential for clauses to reduce the productivity losses associated with part-time work, the lowest part of Table 7 presents the results of the separate estimation for the 2005 and 2007 waves (i.e., before the part-time reform of 2007[26]) and for the 2010 wave (i.e., after the reform). Indeed, if the 2003 Biagi's Law was in the direction of great freedom in the use of clauses by firms, thus favoring them at the expenses of employees, with the subsequent law in 2007, the situation shifted in favor of employees. Since then, the *precise* procedure for using elastic and flexible clauses has had to be agreed on the basis of sectoral collective agreements, into which the needs of individual firms cannot be directly incorporated.[27] The results suggest that when the Biagi's Law was in force (2005 and 2007), using part-time work with clauses decreased productivity by about 47% less than using it without clauses, whereas, using part-time work with clauses in 2010, when the power of firms in relation to the use of clauses was strongly reduced as a result of the 2007 Law, is estimated to have decreased productivity by about 37% less compared to the case in which clauses were not used. These estimates suggest that the capability of clauses to curtail the productivity losses related to part-time work has been substantially reduced as a result of the 2007 Law, by as much as 10 percentage points. This eventually contributes to making firms less willing to grant part-time work to employees who ask for it. An implication of these findings is that introducing more flexibility into the use of part-time work could be a win-win strategy: for firms, which would experience a smaller loss in productivity associated with part-time work, and for workers, since firms would be more willing to offer part-time

[26]Since this reform has been enacted on December 24th, it has virtually started to be applied since 2008.

[27]The Biagi's Law allowed the employers and the employees to directly stipulate flexible and elastic clauses, even in the absence of collective agreements. Starting from 2007, this is no more permitted.

contracts to those workers who wish to have one.

Finally, Table 8 summarizes the results for the separate impacts of part-time work by sector of economic activity. We find that part-time work is detrimental to firm productivity in all the macro categories of industries: manufacturing, construction, trade, transportation and communication, and services. The impact of interest is always statistically significant (at least at the 10% level) and ranges between -0.122 (for manufacturing) and -0.467 (for transportation and communication). When we drill down and consider several sub-industries, we find that only for the retail sector does the impact of part-time work on productivity change its sign, becoming positive, though very small in magnitude (0.006). This result is consistent with the fact that retail shops often have longer opening hours than the typical full-time working time and that they may also experience workload peaks during the day. Under these circumstances, part-time work may have the potential to increase the allocation efficiency, as argued by Künn-Nelen et al. (2013), who report a positive effect for the Dutch pharmacy sector (which belongs to the retail industry). The impact of part-time work also turns positive for the retail sector in the study by Specchia and Vandenberghe (2013). In our case, however, this positive effect is not statistically significant at any conventional level.[28]

7. Conclusions

In this paper, we investigate the impact of part-time work on firm productivity. Due to data-related motivations, we use a two-step procedure. In the first step, we use a large panel data set on (almost) all Italian corporations for the period 2000-2010 to obtain an estimate of the productivity of each firm in each year. We deal with the simultaneity issue concerning the estimation of production functions through the ACF-FE method, which explicitly takes unobserved (time-invariant) firm heterogeneity into account. We then match the productivity estimates with a uniquely rich survey on Italian firms for the years 2005, 2007, and 2010. In the second step of the procedure, we explore the impact of part-time work on firm productivity, controlling for a large set of firm's observable characteristics, for unobserved heterogeneity (FE estimation), and for correlation with productivity shocks (IV estimation).

Our main finding is that part-time work is detrimental to firm productivity: a 10% increase in the share of part-timers is estimated to decrease productivity by 1.45%. These results are consistent with the existence of relevant communication and coordination inefficiencies created by part-time work, eventually leading to a decrease in productivity. Our finding may also stem from intrinsic differences in the underlying individual productivity of

[28]We only have 346 observations for the retail sector.

individuals working a reduced number of hours compared to those working full-time, possibly originated by the presence of start-up costs.

We are the first to explore the separate impacts of horizontal, vertical, and mixed part-time work, finding that the negative impact is mostly exerted by the horizontal component, while for the vertical model we find no significant impact. This suggests that what really damages a firm's productivity is the *daily* reduction in the working time. These findings have broad policy implications. For example, more men could be encouraged to take on vertical part-time work (e.g., working four full-time days per week instead of five) with little disruption for firms and for their own careers and to the advantage of their wives/partners' participation in the labor market and the promotion of gender equality.

Moreover, we find that firms using part-time work to accommodate workers' requests suffer the most from it. In fact, the negative impact on those firms is almost double compared to that on firms that adopt it willingly. An explanation for the fact that firms continue to grant part-time work to employees asking for it despite its detrimental productivity impact may rely on a conscious trade-off between short-run *versus* long-run objectives by the management. In particular, it might be worthwhile from the firm's standpoint to face immediate productivity losses due to the acceptance of a worker's request for a (temporary) shift from a full-time to a part-time position, in order to avoid higher costs in the long run, such as those resulting from workers' dissatisfaction with work arrangements, higher quits of valuable workers, and overall loss of firm reputation in the provision of workers' valued non-monetary benefits.

While the finding that the productivity loss of part-time work is greater if the firm passively adopt it compared to the case in which it actively do so is coherent with expectations, the fact that part-time work also damages firms that willingly use part-time work seems surprising. One reason for this finding may reside in the inability of managers to anticipate correctly the productivity penalties related to part-time work. It may also be the result of a consciously weighed trade-off between productivity losses and cost savings in the presence of pay discrimination against part-timers. We are unable to provide with our data any direct evidence that part-time workers are generally paid less than their full-time counterparts. Italian legislation dictates that workers' remuneration, and any other work-related benefits, is decreased *proportionally* for those working on a part-time basis, suggesting that hourly pay differences among the two types of workers may not compensate for their productivity differentials. While Garnero et al. (2014) report some evidence for Belgium suggesting that the lower pay of part-timers partly compensates their lower productivity, it is unclear whether the firm-level wage equations estimated by these authors can accurately account also for those quasi-fixed labor costs (e.g., training or hiring costs) that increase linearly with the number of workers, rather than with the number of hours worked. Clearly, more empirical evidence on these issues is needed, offering a potentially fruitful area of exploration for future research.

Finally, we find that flexible and elastic clauses are effective in reducing the productivity losses associated with part-time work: the use of such clauses is estimated to decrease its negative impact by about 43%. Considering that a large fraction of firms declare that they use part-time arrangements in response to their employees' requests, these clauses appear to provide an important instrument to increase firms' flexibility in the stodgy usage of part-time work. In this view, flexible and elastic clauses may represent a win-win policy: reducing the negative impact of part-time work on firm productivity, they render firms more prone to concede part-time arrangements to workers who ask for them. Policy makers should consider encouraging a wider use of such practices in countries and sectors where they are not available, as well as promoting a greater degree of flexibility in the existing schemes.

Table 1: **RIL-AIDA data set: distribution of firm-year observations by industry and distribution of firms by number of panel observations**

Industry	**Observations**	**Percentage**
Manufacturing	6,897	49.8
Construction	2,002	14.4
Trade	1,46	10.6
Transportation and communication	1,111	8.0
Services	2,383	17.2
Total	13,860	100
Number of panel observations	**Firms**	**Observations**
1	5,967	5,967
2	2,421	4,842
3	1,017	3,051
Total	9,405	13,860

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

Table 2: **RIL-AIDA data set: sample summary statistics**

Variable	**Mean**	**Standard deviation**
Information from AIDA data set		
Revenues	33,123,111	207,185,847
Value added	7,611,426	33,644,799
Personnel costs	4,596,118	18,639,319
Wages	3,179,241	12,991,786
Capital*	6,067,997	41,796,696
Raw materials	17,784,712	146,538,303
Profit	795,510	16,413,536
Information from RIL data set		
Employees	103.709	396.895
Share of females	0.306	0.245
Share of non-EU workers	0.058	0.110
Share of temporary workers	0.105	0.153
Share of blue-collars	0.593	0.299
Share of white-collars	0.361	0.279
Share of managers	0.046	0.078
Share of workers with college degree**	0.088	0.139
Share of workers with high-school degree**	0.418	0.253
Share of workers with middle-school degree**	0.495	0.297
Share of workers under 25**	0.056	0.087
Share of workers aged between 25 and 34**	0.244	0.179
Share of workers aged between 35 and 49**	0.510	0.192
Share of workers over 50**	0.189	0.148
Information from RIL data set: part-time work		
Share of part-timers	0.084	0.141
Share of female part-timers	0.065	0.115
Share of male part-timers	0.019	0.058
Share of horizontal part-timers	0.070	0.126
Share of vertical part-timers	0.006	0.035
Share of mixed part-timers	0.008	0.051
Share of female and horizontal part-timers	0.056	0.104

Table 2: **RIL-AIDA data set: sample summary statistics - continued**

Variable	**Mean**	**Standard deviation**
Share of female and vertical part-timers	0.004	0.026
Share of female and mixed part-timers	0.005	0.039
Share of male and horizontal part-timers	0.015	0.051
Share of male and vertical part-timers	0.002	0.016
Share of male and mixed part-timers	0.002	0.022
Share of females among part-timers	0.791	0.321
Share of males among part-timers	0.209	0.321
Share of horizontal part-timers among part-timers	0.868	0.294
Share of vertical part-timers among part-timers	0.070	0.215
Share of mixed part-timers among part-timers	0.062	0.214
Share of female and horizontal part-timers among part-timers	0.699	0.375
Share of female and vertical part-timers among part-timers	0.046	0.172
Share of female and mixed part-timers among part-timers	0.046	0.180
Share of male and horizontal part-timers among part-timers	0.170	0.297
Share of male and vertical part-timers among part-timers	0.024	0.118
Share of male and mixed part-timers among part-timers	0.016	0.100
		Number of firm-year observations: 13,860
		Number of firms: 9,405

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)
* Computed according to the permanent inventory method. See Appendix B for details.
** Only for year 2010 (5,912 observations).

Table 3: **RIL-AIDA data set: part-time work; use, types, clauses, and reasons**

	Observations	Percentage
Use of part-time work and clauses		
Use part-time work	9,434	68.1
of which:		
with clauses (elastic and/or flexible)	3,467	36.8
without clauses (elastic and/or flexible)	5,967	63.2
Types of part-time work		
Use horizontal part-time work	8,710	62.8
Use vertical part-time work	1,407	10.2
Use mixed part-time work	1,061	7.7
Flexible and elastic clauses - excluding firms using mixed part-time work		
Use horizontal part-time work	8,041	62.8
of which:		
with flexible clauses	2,721	33.8
without flexible clauses	5,320	66.2
Use vertical part-time work	1,169	9.1
of which:		
with elastic clauses	459	39.3
without elastic clauses	710	60.7
Reasons for the use of part-time work		
Workers' willingness	*6,411*	*68.0*
to accommodate workers' requests for shorter working time	6,411	68.0
Firms' willingness	*2,828*	*30.0*
it is suitable for the production process	1,954	20.7
it is not affordable to employ workers on a full-time basis	449	4.8
it increases labor productivity	232	2.5
to face programmed seasonality	193	2.0
Other reasons	*195*	*2.0*
Other reasons	195	2.0

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

Table 4: **Results; basic model (part-time work); estimation methods: OLS, FE, IV**

	Dependent variable: $\widehat{A}_{it}$ (ACF-FE estimates)										
	1	2	3	4	5	6	7	8	9	10	11
Variable	**OLS1**	**OLS2**	**OLS2010a**	**OLS2010b**	**OLScomp1**	**FE1**	**FE2**	**OLS-comp2**	**IV1**	**IV2**	**OLS-comp3**
Share of part-timers	-0.219***	-0.146***	-0.182***	-0.182***	-0.192***	-0.115*	-0.117*	-0.169***	-0.273***	-0.252***	-0.195**
	(0.030)	(0.031)	(0.049)	(0.049)	(0.049)	(0.063)	(0.066)	(0.055)	(0.104)	(0.095)	(0.078)
Share of females		-0.089***	-0.137***	-0.128***	-0.115***		0.017	-0.126***	-0.144***	-0.148***	-0.158***
		(0.022)	(0.037)	(0.037)	(0.037)		(0.039)	(0.028)	(0.041)	(0.040)	(0.040)
Share of non-EU workers		-0.123***	-0.102*	-0.080	-0.094		0.008	-0.117***	-0.099	-0.099	-0.100
		(0.033)	(0.059)	(0.059)	(0.059)		(0.046)	(0.044)	(0.064)	(0.064)	(0.067)
Share of temporary workers		-0.049*	-0.027	-0.018	0.026		0.161***	0.068	0.140**	0.140***	0.141**
		(0.025)	(0.039)	(0.039)	(0.039)		(0.042)	(0.042)	(0.057)	(0.057)	(0.059)
Share of blue-collars		-0.682***	-0.600***	-0.550***	-0.781***		-0.072	-0.931***	-0.854***	-0.856***	-0.861***
		(0.063)	(0.106)	(0.105)	(0.106)		(0.068)	(0.103)	(0.140)	(0.140)	(0.146)
Share of white-collars		-0.526***	-0.433***	-0.392***	-0.542***		-0.074	-0.772***	-0.554***	-0.556***	-0.563***
		(0.065)	(0.111)	(0.111)	(0.114)		(0.069)	(0.107)	(0.149)	(0.150)	(0.156)
Share of under 25			0.166**	0.184**							
			(0.0787)	(0.079)							
Share of w. aged between 25 and 34			0.094**	0.107**							
			(0.044)	(0.044)							
Share of w. aged between 35 and 49			0.062	0.073*							
			(0.044)	(0.044)							
Share of w. with high-school degree			0.011	0.005							
			(0.026)	(0.026)							
Share of w. with college degree			0.351***	0.334***							
			(0.066)	(0.067)							
Type of the manager				-0.058***							
				(0.017)							
Gender of the manager				-0.047***							
				(0.017)							
Age of the manager				0.060***							
				(0.021)							
Education of the manager				0.003							
				(0.014)							
Size 1 (10-19 employees)	-0.920***	-0.895***	-0.908***	-0.878***	-0.919***			-0.802***	-0.802***	-0.802***	-0.802***
	(0.017)	(0.017)	(0.027)	(0.028)	(0.028)			(0.023)	(0.031)	(0.030)	(0.032)
Size 2 (20-49 employees)	-0.726***	-0.699***	-0.706***	-0.684***	-0.715***			-0.625***	-0.625***	-0.625***	-0.625***
	(0.017)	(0.016)	(0.026)	(0.027)	(0.027)			(0.022)	(0.030)	(0.030)	(0.031)
Size 3 (50-249 employees)	-0.412***	-0.392***	-0.403***	-0.388***	-0.405***			-0.364***	-0.342***	-0.342***	-0.341***
	(0.017)	(0.017)	(0.028)	(0.028)	(0.028)			(0.022)	(0.030)	(0.030)	(0.031)
Year dummies	yes	yes	-	-	-	yes	yes	yes	yes	yes	yes
Region dummies	yes	yes	yes	yes	yes	-	-	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes	-	-	yes	yes	yes	yes
Year/industry dummies	yes	yes	-	-	-	yes	yes	yes	yes	yes	yes
Observations	13,860	13,860	5,216	5,216	5,216	6,989	6,989	6,989	3,536	3,536	3,536
Number of firms	9,405	9,405	5,216	5,216	5,216	3,089	3,089	3,089	2,738	2,738	2,738

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

*Robust standard errors in parentheses; ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. The reference group for blue- and white-collar workers' shares is managers' share; for the age distribution it is the share of workers over 50; for the education distribution it is the share of workers with a middle-school degree; and for size dummies it is more than 250 employees. Region dummies consist of 20 dummies, 1 for each administrative region in Italy; industry dummies account for 199 dummies, 1 for each 3-digit Ateco 2002 industry; and year/industry dummies are the interactions between year and industry dummies, as previously defined. 'Type of the manager' is a dummy that takes value 0 if the manager is the owner and 1 if he/she is an internal/external manager; 'gender of the manager' is a dummy that equals 1 if the manager is a female; 'age of the manager' is a dummy that equals 1 if the manager is over 40; and 'education of the manager' is a dummy that takes value 1 if the manager has a college degree or more.*

Table 5: **Results; extensions: types of part-time work; estimation method: OLS**

Dependent variable: $\widehat{A}_{it}$ *(ACF-FE estimates)*

Share of horizontal part-timers	-0.148***	(0.033)
Share of vertical part-timers	-0.013	(0.101)
Share of mixed part-timers	-0.197**	(0.081)
Number of firm-year observations: 13,860		
Number of firms: 9,405		

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

All the estimations include the same set of controls as in Specification 2 of Table 4. For the rest, see the footnote of Table 4.

Table 6: **Results; extensions: reasons for the use of part-time work; estimation method: OLS**

Dependent variable: $\widehat{A}_{it}$ *(ACF-FE estimates)*

	Workers' requests	**Firms' willingness**
Share of part-timers	-0.254***	-0.134***
	(0.065)	(0.050)
Number of firm-year observations	6,411	2,828

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

The estimates are performed on sub-samples of firm-year observations using part-time work (9,434). To split the sample on the basis of the reasons for part-time use (i.e., either workers' or firm's willingness), we have to remove those observations (amounting to 195) for which the item 'other reasons' has been chosen, since we do not know whether they belong to the first or the second group. All the estimations include the same set of controls as in Specification 2 of Table 4. For the rest, see the footnote of Table 4.

Table 7: **Results; extensions: flexible and/or elastic clauses; estimation method: OLS**

Dependent variable: $\widehat{A}_{it}$ (ACF-FE estimates)

	Flexible and/or elastic clauses	**No clauses**
Share of part-timers	-0.108**	-0.191***
	(0.051)	(0.058)
Number of firm-year observations	3,467	5,967
Only years 2005 and 2007		
Share of part-timers	-0.055	-0.103*
	(0.078)	(0.062)
Number of firm-year observations	2,014	3,123
Only year 2010		
Share of part-timers	-0.170**	-0.271***
	(0.068)	(0.089)
Number of firm-year observations	1,453	2,844

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)
The estimates are performed on sub-samples of firm-year observations using part-time work (9,434). All the estimations include the same set of controls as in Specification 2 of Table 4. For the rest, see the footnote of Table 4.

Table 8: **Results; extensions: industry differentials; estimation method: OLS**

Dependent variable: $\widehat{A}_{it}$ (ACF-FE estimates)

Industry	**Share of part-timers**	**Observations**	**Mean**	**Std. Dev.**
Manufacturing	-0.122**	6,897	0.062	0.089
	(0.050)			
Construction	-0.228*	2,002	0.049	0.075
	(0.118)			
Trade	-0.215**	1,467	0.106	0.140
	(0.091)			
of which: Retail	0.006	346	0.173	0.189
	(0.141)			
Transportation and communication	-0.467**	1,111	0.055	0.094
	(0.186)			
Services	-0.203***	2,383	0.177	0.245
	(0.048)			
				Number of firm-year observations: 13,860
				Number of firms: 9,405

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)
All the estimations include the same set of controls used as in Specification 2 of Table 4. For the rest, see the footnote of Table 4.

Appendices

A. The first step: estimating the firm productivity

To begin with, we assume that the equation relating output to labor and capital inputs aggregates and residual productivity is a production function of the Cobb-Douglas type:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{A.1}$$

where A_{it}, the residual productivity, is modeled as:

$$A_{it} = exp\{\alpha + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it}\} \tag{A.2}$$

where α is the average productivity of the firms; ν_t, μ_j, and σ_r are respectively time-, industry-, and region-specific deviations from that mean; and ω_{it} is the time- and firm-specific (i.e., idiosyncratic) deviation from that mean; whereas ϵ_{it} is a measurement error that is by assumption not correlated with the inputs.

Moreover, we assume that the labor and capital aggregates are not perfectly flexible inputs. Intuitively, this means that the amounts of such inputs to be used in the production process at t are actually decided by the firm at $t-1$. This assumption is consistent with the fact that, on the one hand, new capital takes time to be ordered, delivered, installed, and put into operation and that, on the other hand, it takes time to fire and/or hire workers. In the rest of the discussion, we will refer to this as the 'timing assumption'.

In practice, the production function that we estimate is obtained by using (A.2) and by taking logs in (A.1):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it} \tag{A.3}$$

where lowercase letters indicate natural logarithms.

A crucial issue in estimating production functions lies in the simultaneity of inputs. Labor and capital aggregates are likely to be correlated with the productivity of the firm (i.e., with A_{it}): if the firm faces a positive productivity shock, it may decide to expand its output by increasing its usage of inputs.[29] Notice that, since ν_t, μ_j, and σ_r are easily accounted for by inserting time, industry, and region dummies, the real concern is related to ω_{it} which is unobservable to the econometrician and idiosyncratic to the firm. Hence, the rest of the discussion focuses on ω_{it} rather than on the whole expression for (the log of) A_{it} and, for

[29] We are implicitly assuming that the firm knows (at least partially) its productivity.

the sake of notation, we write the production function as:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{A.4}$$

where y_{it}, l_{it}, and k_{it} are from now on the time-, industry-, and region-demeaned output and labor and capital aggregates.

The simultaneity problem makes OLS estimates of (A.4) and, consequently, of the residual productivity[30], inconsistent. According to the assumptions that are made concerning the structure of ω_{it}, several methods can be used to deal with the simultaneity of inputs. Whether one method is better than another depends on what we consider to be the most realistic set of assumptions for ω_{it}.

If we are willing to believe that ω_{it} is constant over time (i.e., $\omega_{it} = \omega_i$), exploiting the time dimension of our data, we are able to eliminate the simultaneity problem (i.e., ω_i) by running an OLS regression on the within-group transformation of (A.4):

$$\widetilde{y}_{it} = \beta_l \widetilde{l}_{it} + \beta_k \widetilde{k}_{it} + \widetilde{\epsilon}_{it} \tag{A.6}$$

where the tilde operator indicates the within-group transformation: $\tilde{x}_{it} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$.[31]

Since the assumption that ω_{it} is constant over time is rather restrictive, other methods have been developed that try to solve the simultaneity issue while allowing ω_{it} to evolve over time according to a more flexible process. In the context of the control function approach, Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006) are the most notable examples. Since our preferred specification is based on an extended version of the method developed by Ackerberg et al. (2006), we concentrate on it here (for a detailed discussion of the OP and LP methods, see Van Beveren, 2012 and Del Gatto et al., 2011).

In the ACF framework, ω_{it} evolves over time according to a first-order Markov process, its realization at time t is observed by the firm at time t (i.e., contemporaneously) and it is at least partially anticipated by the firms. Since ω_{it} is assumed to follow a first-order Markov process, it is possible to write:

$$E[\omega_{it}|I_{it-1}] = g(\omega_{it-1}) + \xi_{it}$$

[30] According to (3), the (natural) logarithm of the residual productivity for firm i at time t is computed as:

$$lnA_{it} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} \tag{A.5}$$

where $\widehat{\beta}_l$ and $\widehat{\beta}_k$ are the estimated production function coefficients.

[31] This procedure is known as fixed-effects (FE) or within-group regression. Notice that in this case μ_j and σ_r are already removed by the within-group transformation, since they are time invariant.

where I_{it-1} is the information set of firm i at time $t-1$; $g(\cdot)$ is a completely general function and represents the predictable component of ω_{it}; and ξ_{it} is the innovation in the productivity, which, by construction, is unpredictable by the firm, that is, $E[\xi_{it}|I_{it-1}] = 0$. Notice that the assumption that ω_{it} follows a first-order Markov process, relates both to the stochastic process regulating ω_{it} and to the firms' information set. Basically, firms observe ω_{it} at t and form expectations about ω_{it} using $g(\cdot)$ at $t-1$.

The intermediate inputs, m_{it}, are assumed to be perfectly flexible: the choice of the amount of them to be used at t is made at t (i.e., contemporaneously). Moreover, they are assumed not to have any dynamic implication: m_{it} does not depend on m_{it-1}.[32] Furthermore, it is assumed that the demand for intermediate inputs is a function of aggregate labor and capital and firm productivity and that f is strictly increasing in ω_{it}:

$$m_{it} = f(l_{it}, k_{it}, \overset{+}{\omega}_{it}) \tag{A.7}$$

Intuitively, this amounts to requiring that the greater the productivity, the larger the demand for intermediate inputs. If this (strict) monotonicity condition on f holds, it can be inverted out to deliver an expression of ω_{it} as a function of l_{it}, k_{it}, and m_{it}, which are indeed observables:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}) \tag{A.8}$$

This expression for ω_{it} can then be substituted into (A.4) to produce:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{A.9}$$

At this point, ACF propose a two-step strategy to obtain estimates of β_l and β_k. In the first step, y_{it} is non-parametrically regressed against a function in l_{it}, k_{it}, and m_{it}, which we call $\Phi(l_{it}, k_{it}, m_{it})$.[33] From this regression, we can identify the composite term:

$$\widehat{\Phi}_{it} = \widehat{\alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it}}$$

Given guesses of β_l and β_k, that is, β_l^* and β_k^*, it is then possible to obtain the implied ω_{it},

[32]On the contrary, labor and capital aggregates are not restricted to be non-dynamic. Adjustment costs in such inputs are therefore admitted (e.g., hiring/firing costs and capital disposal costs).

[33]In our empirical analysis, we approximate $\Phi(\cdot)$ with a second-order polynomial in l_{it}, k_{it}, and m_{it}. For robustness, we have also tried with higher orders (third- and forth-order polynomials). However, since this does not substantially alter the results, we have decided to use the second-order approximation.

$\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$[34], as:

$$\hat{\omega}_{it}(\beta_l^*, \beta_k^*) = \widehat{\Phi}_{it} - \beta_l^* l_{it} - \beta_k^* k_{it}$$

Recalling that ω_{it} is assumed to follow a first-order Markov process, that is, $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, and given our implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute implied innovations $\hat{\xi}_{it}(\beta_l^*, \beta_k^*,)$ as the residuals from a non-parametric regression of implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$ on implied $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*)$.[35] In the second step of this procedure, the sample analogues of the moment conditions imposed by our model[36] are evaluated:

$$\begin{aligned} \frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*)k_{it} = 0 \\ \frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*)l_{it} = 0 \end{aligned} \tag{A.10}$$

The search over β_l^* and β_k^* continues until $\hat{\beta}_l$ and $\hat{\beta}_k$ are found to satisfy (A.10). These are the ACF estimators of β_l and β_k.

Though the ACF method offers a potential solution to the simultaneity problem, we argue that explicitly accounting for a time-invariant component in the structure of firm productivity, besides the time-varying one, would represent a further enhancement at a relatively low cost. In a nutshell, ACF propose to proxy residual productivity, which is unobservable, through the intermediate inputs' demand. Very powerful though this proxy may be, some of its parts are still likely to be left unexplained. From this perspective, removing the time-invariant part of the productivity would definitely increase the chance of the proxy to work well. Following Vandenberghe et al. (2013), we argue that only the first stage of the ACF procedure needs to be modified to account explicitly for firm fixed effects.

In this framework, residual productivity is modeled as:

$$\omega_{it} = \eta_i + \omega_{it}^* \tag{A.11}$$

According to (A.11), ω_{it} is composed of the sum of a time-invariant (η_i) and a time-varying (ω_{it}^*) components. On the one hand, η_i can be thought of as including firm features such as the managerial quality, the culture of the firm, and its international profile, which can be assumed to be fixed over time, whereas the time-varying component ω_{it}^* can be thought of as an idiosyncratic productivity shock hitting the firm at t. Note that we still assume that ω_{it}^*

[34] Notice that these implied $\omega_{it}'s$ also comprise the constant term α.

[35] In our empirical analysis, we approximate $g(\cdot)$ with a third-order polynomial in $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*)$.

[36] The moment conditions imposed by our model, stemming from the assumption that capital and labor aggregates are not perfectly flexible, are: $E[\xi_{it}k_{it}] = 0$ and $E[\xi_{it}l_{it}] = 0$.

follows a first-order Markov process and that it is partially anticipated by firms. We then assume that the demand for intermediate inputs is given by:

$$m_{it} = f(l_{it}, k_{it}, \omega^*_{it}) \tag{A.12}$$

so that it solely depends on the amount of labor and capital aggregates to be used in t and the productivity shock observed at t. We exclude the demand of intermediate inputs depending on η_i; this assumption rules out factors such as management quality, culture, and internationalization of the firm contributing to determining the demand for the intermediate goods to be used in the production process. This does not seem to be an implausible assumption, since it is reasonable to think that the demand for intermediate inputs, which are by assumption perfectly flexible and non-dynamic, depends only on time-varying components. Moreover, we preserve the assumption that f is invertible in ω^*_{it}. This set of assumptions implies that Equation (A.9) is modified as follows:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + \eta_i + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{A.13}$$

As before, by setting $\Phi(l_{it}, k_{it}, m_{it}) \equiv \alpha + \beta l_{it} + \beta k_{it} + f^{-1}(l_{it}, k_{it}, m_{it})$, we can write (A.13) as:

$$y_{it} = \Phi(l_{it}, k_{it}, m_{it}) + \eta_i + \epsilon_{it} \tag{A.14}$$

At this point, we are able to remove η_i from (A.14) by applying (non-parametric) FE estimation.[37] From the FE estimation of (A.14), we are able to obtain a consistent estimate of $\Phi(\cdot)$, that is, $\hat{\Phi}(\cdot)$, so that it is possible to proceed to the (unchanged with respect to the ACF method) second stage of the estimation from: $\widehat{\Phi}_{it} = \widehat{\alpha + \beta_l l_{it} + \beta_k k_{it} + \omega^*_{it}}$.

[37] In the empirical analysis, we again approximate $\Phi(\cdot)$ with a second-order polynomial in l_{it}, k_{it}, and m_{it}. Notice that, as in the simple FE case, μ_j and σ_r are already removed by the non-parametric FE estimation, since they are time invariant.

B. The AIDA data set

The data set used in our analysis is the result of some cleaning compared to the original version. We remove firms belonging to the mining industry (there are a few) and to sectors in which the level of public intervention is substantial, such as the production and distribution of electricity, gas, and water and garbage disposal. We restrict the attention to firms classified as 'active' and to firms with average revenues greater than 50,000 euros per year. To be able to estimate the production functions, we are forced to remove observations for which value added, capital, personnel costs, and materials expenditures have missing, negative, or zero values. Finally, to perform LP, ACF, and ACF-FE estimations, we have to restrict our attention to firms for which we have at least 2 *consecutive* years of observations.

The final data set is made up of 2,406,612 firm-year observations for 440,953 firms. While for 8.1% of the firms we have the complete observation window (11 years), for half of them we have more than 5 years of observations. Table B.1 shows the distribution of the AIDA data set across the 40 sectors (2-digit Ateco 2002 classification) for which we estimate a separate production function. As shown in Table B.1, about one-third of the observations belong to the manufacturing industry. The trade and services sectors cover respectively about 29% and 21% of the observations, while the remaining observations are split between the construction industry (14.1%) and the transportation and communication industry (4.2%).

Table B.1: **AIDA data set: distribution of firm-year observations by sector of economic activity (2-digit Ateco 2002)**

Sector of economic activity	Frequence	Percentage
Manufacturing	*783,129*	*32.5*
Food and beverage	59,613	2.5
Tobacco	146	0.0
Textile	42,434	1.8
Clothing	30,543	1.3
Leather and leather goods	28,837	1.2
Wood and wood products (excluding furniture)	23,615	1.0
Paper and paper product	14,900	0.6
Printing and publishing	37,295	1.6
Coke and petroleum products	2,016	0.1
Chemical products	27,386	1.1
Rubber and plastics	37,835	1.6
Non-ferrous production	44,267	1.8
Ferrous production	15,307	0.6
Ferrous products (excluding machinery)	150,075	6.2
Machinery products	108,722	4.5
Office machinery and computers	6,240	0.3
Electrical machinery	33,566	1.4
Radio, TV and TLC equipment	12,614	0.5
Medical equipment and measurement instruments	22,407	0.9

Table B.1: **AIDA data set: distribution of firm-year observations by sector of economic activity (2-digit Ateco 2002) - continued**

Sector of economic activity	**Frequence**	**Percentage**
Motor vehicles	9,942	0.4
Other transportation equipment	10,824	0.4
Furniture and other manufacturing industries	58,161	2.4
Recycling	6,384	0.3
Construction	*339,776*	*14.1*
Construction	339,776	14.1
Trade	*688,506*	*28.6*
Trade and maintenance of motor vehicles	95,059	4.0
Wholesale (excluding motor vehicles)	373,492	15.5
Retail (excluding motor vehicles)	219,955	9.1
Transportation and communication	*100,544*	*4.2*
Land transportation/transportation by pipeline	53,030	2.2
Maritime transportation	1,973	0.1
Air transport	578	0.0
Auxiliary transportation activities	40,775	1.7
Post and telecommunication	4,188	0.2
Services	*494,657*	*20.6*
Hotels and restaurants	121,228	5.0
Real estate	67,876	2.8
Rental services	10,723	0.5
Computer and related activities	83,998	3.5
R&D	3,959	0.2
Business services	155,951	6.5
Recreational, cultural, and sport activities	36,411	1.5
Household services	14,511	0.6
Total	2,406,612	100

Source: AIDA data set (period: 2000-2010)

C. The productivity estimates

Table C.1 shows the correlation matrix of the different productivity estimates, while Table C.2 shows their summary statistics. The different productivity estimates are positively and highly correlated: the correlation coefficients range between 0.826 and 0.968 (for a similar finding, see Van Beveren, 2012). The ACF and ACF-FE estimates are very similar compared to the OLS estimates (the correlation coefficients are 0.968 and 0.948, respectively). As expected, given the high correlations, their summary statistics are quite similar. The mean of the (natural logarithm of the) productivity estimates ranges between 3.061 for the OLS estimates and 5.506 for the FE estimates. This suggests that the simultaneity issue, though conceptually relevant, loses part of its importance in practice. Still, its relevance and, consequently, the empirical validity of the methods trying to deal with it should be assessed in view of the conclusions that they lead to in analyzing the impact of interest (see Appendix D, Table D.1).

Table C.1: **AIDA data set: correlation matrix of the different productivity estimates (OLS, FE, LP, ACF, ACF-FE)**

Productivity estimates	OLS	FE	LP	ACF	ACF-FE
OLS	1.000				
FE	0.857	1.000			
LP	0.863	0.845	1.000		
ACF	0.968	0.898	0.871	1.000	
ACF-FE	0.948	0.928	0.826	0.958	1.000
Number of firm-year observations: 2,406,612					
Number of firms: 440,953					

Source: AIDA data set (period: 2000-2010)

Table C.2: **AIDA data set: summary statistics of the different productivity estimates (OLS, FE, LP, ACF, ACF-FE)**

Productivity estimates	**Mean**	**Standard deviation**
OLS	3.061	1.106
FE	5.506	1.241
LP	5.205	1.176
ACF	3.694	1.143
ACF-FE	3.924	1.356
Number of firm-year observations: 2,406,612		
Number of firms: 440,953		

Source: AIDA data set (period: 2000-2010)

D. Robustness checks

As a robustness check, we perform OLS estimation restricting the attention to the pre-crisis period (i.e., 2005 and 2007). The results confirm that the productivity effect of part-time work is also significantly negative (at the 5% level) for the pre-crisis period and not substantially different from the general effect (-0.099 *versus* -0.146).

Table D.1 shows the results for the impact of part-time work on the different sets of productivity estimates (i.e., OLS, FE, LP, ACF, and ACF-FE). Not surprisingly, considering the generally high correlations among the different productivity estimates, we find that the predicted impact of part-time work is negative, regardless of which first-step estimation method is used. However, the magnitude of the impact differs somewhat across the methods, ranging between -0.233, when the LP estimates are considered, and -0.091, when productivity is estimated through OLS. Interestingly, our reference method (i.e., the ACF-FE) delivers quite similar estimates of the impact of interest compared to those stemming from the OLS estimation of productivity. On the contrary, the FE and LP estimations, which are most likely to suffer from the well-known problem of downward bias for the FE case and collinearity for the LP case, deliver more different estimates compared to the ACF-FE method.

Table D.1: **Results; robustness checks: OLS, FE, LP, and ACF estimates of productivity as dependent variables; estimation method: OLS**

Productivity estimation method	OLS	FE	LP	ACF	ACF-FE
Share of part-timers	-0.091***	-0.233***	-0.217***	-0.125***	-0.146***
	(0.030)	(0.034)	(0.032)	(0.030)	(0.031)
Absolute difference from ACF-FE estimate	0.055	0.087	0.071	0.022	-
Number of firm-year observations: 13,860					
Number of firms: 9,405					

Source: RIL-AIDA data set (years: 2005, 2007, and 2010)

The estimation includes the same set of controls as in Specification 2 of Table 4. For the rest, see the footnote of Table 4.

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